2D CNN-Based Link Prediction in Opportunistic Networks

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Abstract. Opportunistic Networks are mobile wireless networks without fixed infrastructure, presenting unique challenges for link prediction tasks in computer networks. Although several approaches have been proposed to address this problem, the application of such techniques in opportunistic networks remains a promising strategy for improving packet delivery. This paper presents an analysis of a two-dimensional convolutional neural network architecture for link prediction in opportunistic networks. The experiments were conducted using three real-world datasets: ITC, Infocom06, and MIT Reality Mining. The model achieved competitive performance across all datasets, with AUC values of 0.9929, 0.9833, and 0.9812, and PRAUC values of 0.8777, 0.8321, and 0.8921, respectively. Additionally, experiments were conducted to evaluate link prediction across multiple future intervals, aiming to assess the feasibility of longer-term predictions to support packet forwarding in opportunistic networks. The results indicate that long-term prediction has the potential to enhance routing protocols by improving forwarding decisions.

Keywords: Opportunistic Networks · Link Prediction · Machine Learning · Deep Learning · CNN

1 Introduction

Opportunistic networks are a subclass of Delay Tolerant Networks (DTNs) in which continuous end-to-end connectivity cannot be guaranteed and delayed packet delivery is acceptable. In these networks, communication occurs in the absence of fixed infrastructure and relies on mobile nodes equipped with short-range wireless interfaces, such as Bluetooth. In such environments, a direct path between a source and a destination is often unavailable. Consequently, nodes depend on opportunistic encounters with other nodes to establish temporary communication links and enable packet forwarding. This characteristic gives rise to the term "opportunistic", as communication takes place by exploiting transmission opportunities whenever they arise. To achieve message dissemination

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under these conditions, nodes adopt the store-carry-forward paradigm, in which packets are temporarily stored, physically carried during node mobility, and forwarded only when a suitable contact opportunity becomes available. This operational model makes opportunistic networks particularly well suited for environments characterized by intermittent, sparse, or entirely absent connectivity [10].

Nevertheless, nodes in opportunistic networks typically operate under severe resource constraints, particularly with respect to energy supply and storage capacity. As a result, these resources must be carefully managed to prevent premature node depletion and the consequent drop of buffered packets. In this context, a challenge in forwarding protocols is selecting the next-hop node responsible for carrying a packet closer to its destination. Therefore, designing forwarding strategies that maintain an adequate delivery ratio while avoiding excessive resource consumption remains a widely studied problem in opportunistic networking.

The literature provides numerous examples of situations in which users can benefit from opportunistic communication, including disaster situations [1, 2, 9, 10, 16], battlefields [1, 2, 5, 10, 28], overloaded cellular networks [33, 34] and industrial environments [17]. In these contexts, the store-carry-forward routing paradigm is implemented through intermediate nodes. This mechanism is supported by an additional network layer called the bundle, or packet layer, positioned between the transport and application layers. This layer enables nodes to store complete packets or their fragments, facilitating data delivery despite intermittent connectivity [18].

In addition, link prediction is a traditional problem in computer networks that aims to forecast future connections between nodes. Based on the spatial and temporal characteristics observed in the network, predicting such connections is particularly challenging in opportunistic environments due to node mobility and the possibility of abrupt disconnections, for example, caused by battery depletion. Despite these challenges, accurate link prediction can significantly assist routing algorithms in selecting the most appropriate next-hop node. Improved prediction quality leads to more efficient forwarding strategies, enabling higher packet delivery rates to the destination while reducing overall network resource consumption [14].

One approach to link prediction in networks is the use of machine learning techniques. This approach allows artificial intelligence models to be trained on historical network data and, after learning underlying patterns of network behavior, to predict the existence of future links between nodes.

The primary contributions of this paper are twofold. First, a two-dimensional convolutional neural network is employed for link prediction on real-world opportunistic network datasets, demonstrating its ability to capture spatial-temporal interaction patterns. Second, an analysis of link prediction over multiple future time intervals is provided, showing that the proposed approach maintains strong predictive performance even for longer prediction horizons.

The remainder of this article is organized as follows. Section 2 formalizes the link prediction problem in opportunistic networks and describes the adopted methodology. Section 3 reviews related work on link prediction in opportunistic networks using machine learning techniques. Section 4 presents the experimental setup, reports the obtained results, and provides an analysis with existing approaches. Section 5 discusses the results, and Sect. 6 concludes the article.

2 Link Prediction in Opportunistic Networks

Machine learning techniques have been widely applied in dynamic networks, where long-term link prediction is particularly challenging [6]. The use of deep learning for link prediction offers several advantages, as these models are capable of automatically capturing intrinsic patterns in data, eliminating the need for manual feature engineering and reducing the analytical effort required [3].

According to [27], to formulate the link prediction problem as a machine learning task, an opportunistic network can be represented as a sequence of adjacency matrices $A^{1:T} = \{A^1, A^2, \ldots, A^i, \ldots, A^T\}$, where each matrix A^i represents a matrix whose indices correspond to the network nodes at a time interval i ($i \in \{1, 2, \ldots, T\}$). In this representation, if a connection exists between two nodes a and b, then $A^i(a, b) = 1$; otherwise, $A^i(a, b) = 0$. Following the formulation in [25], the link prediction problem is defined as follows: given a sequence of adjacency matrices, $A^{t:t+\tau-1} = \{A^t, A^{t+1}, \ldots, A^{t+\tau-1}\}$, the objective is to predict the subsequent γ matrices $A^{t+\tau:t+\tau+\gamma-1} = \{A^{t+\tau}, A^{t+\tau+1}, \ldots, A^{t+\tau+\gamma-1}\}$, where t denotes the initial time interval, τ denotes the length of the input sequence, and γ denotes the length of the output sequence. The overall structure is illustrated in Fig. 1.

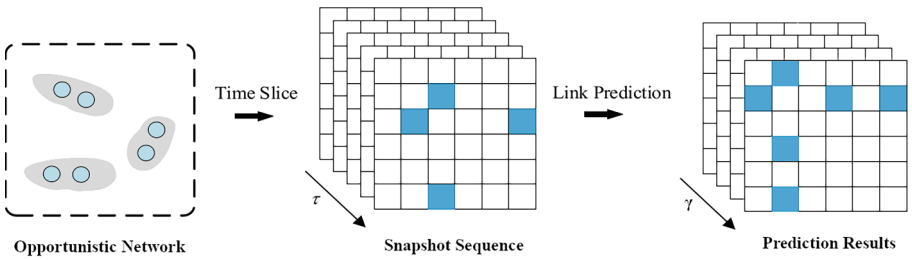

Fig. 1. Adjacency matrices' prediction. Adapted from [25].

Thus, the link prediction task can be formulated as a binary classification problem applied to the entries of the adjacency matrix, where the value 1 indicates the presence of a link and the value 0 indicates its absence.

2.1 Evaluation Metrics

This section introduces two evaluation metrics used to assess the prediction performance in this study. According to [25], the area under the receiver operating characteristic curve (AUC) is widely used for evaluating classification models. The metric is defined as

$$AUC = \frac{n' + 0.5n''}{n}, \tag{1}$$

where n is the number of comparisons in a sample, n' is the number of comparisons in which the predicted value for an existing link is greater than that for a non-existing link, and n'' is the number of comparisons in which both values are equal. The main advantage of this metric is that it provides a performance measure independent of the classification threshold, as well as being less sensitive to misclassification costs and class imbalance.

The area under the precision-recall curve (PRAUC) is commonly used to evaluate performance in sparse or highly imbalanced settings. According to [25], it can be computed as

$$PRAUC = \frac{1}{N} \sum_{u=1}^{N} \sum_{v=1}^{N} \frac{|A(u,v) = 1 \cap P(u,v) = 1|}{|A(u,v) = 1|}, \tag{2}$$

where $A(u,v) = 1$ indicates the existence of a link between nodes u and v, and $P(u,v) = 1$ indicates that a link between these nodes is predicted to exist. In highly imbalanced datasets, PRAUC is preferred because it directly evaluates the classifier's performance on the positive class, which is typically rare. By jointly emphasizing precision and recall, it provides a more informative assessment of the model's ability to identify positive instances. Both AUC and PRAUC range from 0 to 1, where 1 corresponds to the best possible performance.

3 Related Work

In recent years, link prediction in opportunistic networks has been extensively studied using machine learning techniques, involving a variety of datasets, models, and evaluation metrics.

Early approaches primarily relied on Recurrent Neural Networks (RNNs) to model temporal dependencies in node interactions. For example, [4] proposed a link prediction RNN-based method, in which the interaction history between node pairs is divided into network snapshots and represented as sequences of vectors. These sequences are used as input to a model called RNN-LP, which captures the hidden features of the vector sequence, enabling the correlation between nodes to be learned and the connection-formation patterns (which change frequently in opportunistic networks) to be extracted. To address well-known limitations of standard RNNs, such as vanishing gradients and difficulty in modeling long-term dependencies, the authors employed Long Short-Term Memory (LSTM) units. The model was evaluated using only the ITC dataset [21], achieving an AUC of 0.9780.

[15] proposed a link prediction model called BRRN-LP, which represents connection information as correlation vectors, where the correlation reflects the frequency and duration of node interactions. The model is based on a Bayesian Recurrent Neural Network (BRNN), specifically a Bayesian LSTM, which incorporates uncertainty into the network parameters while using gating mechanisms to preserve relevant temporal information. By estimating the posterior distribution of the network weights, the approach aims to improve robustness and reduce model complexity. The model was evaluated using only the MIT Reality Mining dataset [7], considering AUC and precision metrics, and achieved an AUC of 0.985.

[31] proposed a link prediction approach based on Deep Belief Networks (DBNs). In this method, traditional similarity metrics, including Katz Index, Resource Allocation, Adamic-Adar, and Common Neighbor, are used to construct input feature vectors for the DBN, focusing on non-repeated links. The DBN is formed by stacking multiple Restricted Boltzmann Machines (RBMs), trained in a greedy layer-wise manner, enabling the extraction of hierarchical representations from the data. The network is divided into temporal snapshots (10-min and 30-min intervals), from which adjacency matrices are generated. The model was evaluated using only the ITC dataset, achieving an AUC of 0.98.

[13] proposed a method that combines a Markov transition probability matrix with a similarity index matrix called improved random walk with restart (IRWR). The opportunistic network is divided into snapshots, and a similarity matrix is computed for each snapshot. The proposed model is called IRWR-DBN, since it uses a DBN that extracts the temporal characteristics of the network. The model was evaluated on the ITC and MIT Reality datasets using AUC and precision metrics. It achieved an AUC of 0.9591 on the ITC dataset and 0.9789 on the MIT Reality dataset.

More recent studies have shifted toward end-to-end deep learning models that jointly learn spatial and temporal representations. In [23], a correlation factor based on the number and duration of connections between nodes is used to assign weights to the links in the adjacency matrix of the opportunistic network. These matrices, computed over different time intervals, are then combined to form a three-dimensional structure. The proposed architecture consists of five convolutional layers, two fully connected layers, and an output layer. For evaluation, only the ITC dataset was used, and performance was assessed using accuracy and precision metrics.

In [25], the authors proposed a link prediction model based on the Transformer framework, composed of four main components: a topology feature extractor, a temporal feature extractor, a feature fusion module, and a vector mapping model. An attention mechanism is employed to extract topological features by aggregating information from neighboring nodes, enabling the model to learn long-term temporal dependencies and capture global network evolution patterns. The topological and temporal features are then fused, and the resulting feature vectors are mapped to predict the future network topology. The model was evaluated on the ITC, MIT, and Infocom06 [21] datasets using AUC and

PRAUC metrics. For the ITC dataset, the model achieved an AUC of 0.9708 and a PRAUC of 0.8915; for the Infocom06 dataset, it obtained an AUC of 0.9580 and a PRAUC of 0.7240; and for the MIT dataset, the results were an AUC of 0.9738 and a PRAUC of 0.8717.

In [22], the authors proposed a link prediction model called Continuous-graph Attentional Neural Networks for temporal link prediction (LP-CGA). The model is built upon an autoencoder architecture and integrates graph neural networks with attention-based ordinary differential equations. Experiments were conducted using the ITC and Infocom06 datasets, where opportunistic networks were represented as adjacency matrices. Model performance was evaluated using AUC and PRAUC metrics. For the ITC dataset, the model achieved an AUC of 0.9576 and a PRAUC of 0.8907, while for the Infocom06 dataset, it obtained an AUC of 0.9493 and a PRAUC of 0.7366.

In [12], a link prediction method for dynamic networks based on a Continuous Gated Recurrent Graph Convolutional Network (CGR-GCN) was proposed. The approach utilizes common neighbor indices and link attributes to capture network information. The authors incorporate Neural Ordinary Differential Equations (NODEs) into a Temporal Graph Convolutional Network (T-GCN), which combines graph neural networks with RNNs, and introduce a module designed to extract both short- and long-term spatio-temporal features. The model learns the network evolution locally through a graph convolutional network that employs gated recurrent units and NODEs. It then applies temporal convolutions with linear gates to extract global spatiotemporal features. Finally, link prediction is performed in the dynamic network using a fully connected dense neural network. The approach is based on the idea that traditional RNNs handle network snapshots in a discrete manner, limiting their ability to learn continuous dynamics. The authors argue that many existing methods rely solely on adjacency matrices, neglecting important information about link dynamics within snapshots. The model was evaluated on the ITC, Hyccups, and MIT Reality datasets using AUC, PRAUC, and F1-score metrics and compared with other methods. For the ITC dataset, the model achieved an AUC of 0.9681 and a PRAUC of 0.8653, while for the MIT dataset, it achieved an AUC of 0.9434 and a PRAUC of 0.8570.

Hybrid architectures that combine attention mechanisms, temporal convolutions, and graph-based representations have also been proposed. [24] proposed a link prediction method based on spatiotemporal attention mechanisms and temporal convolutional networks, called the Spatial-Temporal Attention and Temporal Convolutional Network (STA-TCN). The approach partitions opportunistic networks into discrete snapshots and uses a state matrix derived from the adjacency matrix, link occurrence frequency, and link duration. Attention and convolutional mechanisms are integrated into an encoder–decoder structure, followed by a fully connected dense neural network. To further enhance prediction performance, the authors transform autocorrelated errors into uncorrelated ones. The proposed method was evaluated using the ITC, MIT, and Infocom06 datasets. The metrics evaluated were AUC, precision, and F1-score. The model

achieved an AUC of 0.9644 on the ITC dataset, 0.9105 on the Infocom06 dataset, and 0.9789 on the MIT dataset.

Among the existing approaches, [27] compared several machine learning methods for link prediction in opportunistic networks, including artificial neural networks, convolutional neural networks (CNNs), RNNs, and attention-based models. The experiments were performed using the ITC and the Infocom06 datasets and evaluated performance in terms of accuracy, precision, recall, F1-score, AUC, and PRAUC. The authors concluded that CNNs employing two-dimensional convolutions represent a promising approach for link prediction in opportunistic networks, as they provide a good balance between predictive performance and architectural simplicity when compared to more complex models such as transformers and continuous-time graph neural networks (GNN). For the ITC dataset, the model achieved an AUC of 0.9840 and a PRAUC of 0.7893, while for Infocom06, it obtained an AUC of 0.9831 and a PRAUC of 0.8321.

[32] proposed a dynamic link prediction framework, named CLTGAT, which integrates contrastive learning (CL) with temporal graph attention network (TGAT). Contrastive learning is an unsupervised approach for graph representation learning. Unlike approaches based on sequences of adjacency matrices, CLTGAT employs duration-driven measures to select positive samples. The model captures network dynamics by modeling two types of temporal events: connections and disconnections. The framework was evaluated using AUC and PRAUC metrics on the Infocom05, Hyccups, and Infocom06 datasets. On the Infocom06 dataset, it achieved an AUC of 0.965 and a PRAUC of 0.962.

In addition to prediction-focused models, some studies incorporate link prediction into routing strategies. For example, [26] proposed EQ-STAR, an energy-efficient routing approach that combines encounter probability estimation with energy-aware optimization to enhance network performance. The method integrates GNNs and reinforcement learning (RL) to identify high-quality reachable paths between nodes, intending to maximize encounter probabilities while minimizing and balancing energy consumption. To estimate encounter probabilities, the approach employs the DySAT-pro model, which captures periodic patterns in the network. Subsequently, an energy-efficient quality Markov decision process (EQ-MDP) is used to jointly optimize energy consumption and encounter probabilities, enabling the selection of the most suitable paths between source and destination nodes. The next-hop relay node is then selected based on the reachable path obtained from the EQ-MDP. The proposed DySAT-pro model was evaluated on the Infocom05 and Infocom06 datasets using AUC, PRAUC, and F1-score metrics. On the Infocom06 dataset, it achieved an AUC of 0.8611 and a PRAUC of 0.8507.

[30] proposed a routing protocol for maritime opportunistic networks that employs encounter probabilities, mobility information, node resource availability, and link state prediction to guide routing decisions. The protocol first estimates the future connectivity status between a node and its neighbors using a link prediction method. When the predicted connectivity equals 1, the remaining features are used to prioritize packet forwarding. The proposed prediction

scheme, named CNN-EAA, combines CNN with an attention mechanism called Effective Additive Attention (EAA), comprising a convolutional encoder and a SwiftFormer-based encoder. The CNN is then trained using a synthetically generated maritime communication dataset. Although the overall routing protocol was evaluated, the study does not report results based on prediction-specific performance metrics.

[11] proposed a link prediction method based on Graph-BERT, in which the original network graph is decomposed into a set of local subgraphs. Each subgraph is constructed around a primary node and a fixed number of the most relevant neighboring nodes, selected based on a similarity criterion. This selection is performed using a top-K strategy, analogous to the KNN algorithm. The resulting subgraphs are used as input during both the training and testing phases. A transformer-based architecture is then used to encode and decode node features. Based on the learned representations, the model estimates the probability of link existence between pairs of nodes. To evaluate the effectiveness of the proposed approach, the authors conducted experiments on a synthetic dataset, using accuracy as the evaluation metric.

Table 1 shows a comparison between the related works on link prediction in opportunistic networks. It can be observed that a wide range of machine learning techniques has been employed in related work for the task of link prediction in opportunistic networks. The AUC metric is the most commonly used to evaluate predictions, while PRAUC is also widely adopted. The ITC, Infocom06, and MIT Reality datasets are extensively used for link prediction in opportunistic networks.

Table 1. Summary of Related Work on Link Prediction in Opportunistic Networks

Ref.	Model	Metrics	Dataset
[4]	LSTM	AUC	ITC
[15]	BRNN	AUC, Precision	MIT Reality
[31]	DBN	AUC	ITC
[13]	DBN	AUC, Precision	ITC, MIT Reality
[23]	Conv3D	Accuracy, Precision	ITC
[25]	Transformer	AUC, PRAUC	ITC, MIT Reality, Infocom06
[22]	GNN+Attention	AUC, PRAUC	ITC, Infocom06
[12]	GCN	AUC, PRAUC, F1	ITC, Hyccups, MIT Reality
[24]	CNN+Attention	AUC, Precision, F1	ITC, MIT Reality, Infocom06
[27]	2D CNN	Accuracy, Precision, Recall, F1, AUC, PRAUC	ITC, Infocom06
[32]	CL+TGAT	AUC, PRAUC	Infocom05, Hyccups, Infocom06
[26]	GNN+RL	AUC, PRAUC, F1-score	Infocom05, Infocom06
[30]	CNN+Attention	-	-
[11]	Transformer	Accuracy	-
This work	2D CNN	AUC, PRAUC	ITC, MIT Reality, Infocom06

Overall, the literature shows a clear progression from sequential and feature-engineered methods to more advanced deep learning architectures capable of modeling spatiotemporal dynamics. Nevertheless, two main limitations can be

identified. First, many studies evaluate their models on a limited set of datasets, which limits a comprehensive assessment of model generalization. Second, the existing works primarily focus on short-term link prediction, with limited or no exploration of multi-step forecasting and long-term temporal dynamics.

To address these gaps, this work extends the evaluation of the 2D CNN model proposed in [27] by considering more real-world datasets, including the MIT Reality Mining dataset, which was not previously explored. In addition, both single-step and multi-step link prediction are investigated, enabling an analysis of performance degradation over longer prediction horizons. This broader evaluation provides a more complete understanding of the model's robustness and its ability to capture long-term temporal dependencies in opportunistic networks.

4 Link Prediction Methodology and Experiments

The use of appropriate machine learning techniques can yield superior results in link prediction. Accurate link prediction can be used to select the next forwarding node more effectively, enabling informed decisions that enhance delivery rates while reducing delay and overhead in opportunistic networks.

This study adopts the two-dimensional convolutional neural network model proposed by [27], reproducing the original evaluation on the ITC and Infocom06 datasets. In addition, the analysis is extended to the MIT Reality Mining dataset, which is introduced in this study as a novel testbed for link prediction in opportunistic networks. Furthermore, this work investigates link prediction across multiple future matrices, a scenario not addressed in the previously discussed studies.

4.1 Datasets

Both the ITC [21] and Infocom06 [21] datasets contain encounter (connection) logs collected from small Bluetooth-enabled devices known as "iMotes". These datasets were preprocessed into a standardized format in which each record contains the identifiers of the two nodes and the start and end times of their contact.

The ITC dataset recorded, over twelve days, the encounters among fifty iMotes on the campus of the University of Cambridge. The deployment included both mobile devices carried by students and fixed devices installed in locations such as bars, markets, shopping centers, and the reception area of the computing laboratory. The resulting dataset, in the standardized format described above, contains 10,776 contact records.

The Infocom06 dataset recorded, over a period of four days, the movement of 98 portable devices deployed during the IEEE Infocom 2006 Conference in Barcelona. The dataset includes seventy-eight mobile iMotes, with an estimated communication range of approximately thirty meters, and twenty stationary iMotes, with a range of approximately one hundred meters. In the standardized format described previously, the dataset contains 227,657 contact records.

The MIT Reality Mining [7] dataset contains data collected at the Massachusetts Institute of Technology using ninety-eight Nokia 6600 smartphones distributed to students from the MIT Media Laboratory and the MIT Sloan School of Management. Data were collected between July 27, 2004, and May 5, 2005, and the provided file corresponds to a database dump containing anonymized data. The database comprises multiple tables, each corresponding to a specific type of collected information. By querying the database, a text file was generated in the same format as the other two datasets. The resulting file contains 145,172 encounter records in the previously described format. In this work, a ten-day subset of the dataset was extracted to ensure a temporal length comparable to that of the other two datasets.

4.2 Single Matrix Prediction

For the conducted experiments, the parameter settings reported by [25] were adopted. Specifically, the ITC and MIT Reality datasets were partitioned into 300-s intervals to construct the adjacency matrices, whereas the Infocom06 dataset was partitioned into 270-s intervals. All experiments were conducted using an input sequence of 10 adjacency matrices to predict a single future matrix as output. Using the predefined notation, given the input adjacency matrices, $A^{t:t+9} = \{A^t, A^{t+1}, \ldots, A^{t+9}\}$, the model predicts the subsequent matrix A^{t+10}.

The Infocom06 and the MIT datasets were partitioned according to time into training, validation, and test sets using an 80%–10%–10% split, respectively. Similarly, the ITC dataset was divided using a 70%–15%–15% split for training, validation, and testing, respectively.

As described by [27], the employed 2D CNN architecture consists of three intermediate Conv2d layers, each followed by a dropout layer to mitigate overfitting by randomly deactivating a fraction of the neurons. Circular padding was adopted, a technique originally designed for omnidirectional images, which reduces the information loss that may occur with conventional padding strategies such as "zero" or "same". Using circular padding on the horizontal axis, for example, the left border of the image is filled with the rightmost region of the image, and vice versa [29]. In this way, this technique uses information from opposite edges and ensures that the padding kernels have the same behavior inside and at the edges of the images [20]. In the convolutional layers, a kernel size of 3 and a stride size of 1 were used. The model was trained using the binary cross-entropy loss function (BCEWithLogitsLoss) and optimized with the Adam optimizer, with a learning rate of 0.001.

In this study, the model was trained using an early stopping strategy with a patience of 10 epochs. Training was terminated when the validation loss did not improve for 10 consecutive epochs, thereby helping to mitigate overfitting. The construction of adjacency matrices was refined at the boundaries of the training, validation, and test intervals to provide a more accurate representation of the network dynamics. Additionally, the network was represented using only the upper triangular portion of the matrices, under the assumption that encounters are symmetric; that is, when node A encounters node B, node B is also considered

to encounter node A. The experimental results obtained using the 2D CNN model are presented in Table 2.

Table 2. Results of Link Prediction Using the 2D CNN Model

	ITC	Infocom06	MIT
AUC	0.9929	0.9833	0.9812
PRAUC	0.8777	0.8321	0.8921

Results reported in related studies using the ITC, Infocom06, and MIT datasets, as previously described, are presented in Table 3 alongside the results obtained in this study. Cells left empty indicate metrics that were not reported in the corresponding works. For the ITC dataset, the 2D CNN model achieved AUC values higher than those reported by [4,12,13,22,24,25,27,31]. In addition, it achieved PRAUC values exceeding those reported in [12,27]. For the Infocom06 dataset, the model obtained AUC values higher than all compared studies [22,24–27,32], as well as PRAUC values higher than those reported in [22,24,25,27]. Finally, Table 3 shows that, for the MIT Reality Mining dataset, the model achieved higher AUC and PRAUC values compared to related studies [12,13,24,25].

The results presented in Table 3 indicate that the 2D CNN model consistently outperforms those reported in several related studies, demonstrating strong predictive performance across all considered datasets, particularly on the MIT Reality dataset. In cases where other approaches surpass the proposed model, the performance differences are generally marginal. A notable exception is the PRAUC reported by [32], which is considerably higher than that achieved by the 2D CNN on the Infocom06 dataset.

However, it is important to note that the approach in [32] relies on contrastive learning combined with a temporal graph attention network, a substantially more complex and computationally demanding architecture, especially during training. This increased cost originates from the integration of temporal attention mechanisms and contrastive objectives, which require additional sampling, multiple forward passes, and pairwise comparisons between embeddings.

Overall, these findings indicate that two-dimensional convolutional neural networks constitute a robust and promising approach for link prediction in opportunistic networks, offering competitive predictive performance while maintaining significantly lower computational complexity.

4.3 Multiple Matrices' Predictions

Link prediction in opportunistic networks seeks to take advantage of predicted connectivity information to support packet forwarding decisions within routing protocols. Given that each adjacency matrix represents a relatively short time interval (270 s or 300 s), a single predicted matrix may not provide sufficient

Table 3. Link Prediction Results

Ref.	ITC		Infocom06		MIT	
	AUC	PRAUC	AUC	PRAUC	AUC	PRAUC
[4]	0.9780	-	-	-	-	-
[15]	-	-	-	-	0.9850	-
[31]	0.9800	-	-	-	-	-
[13]	0.9591	-	-	-	0.9789	-
[25]	0.9708	0.8915	0.9580	0.7240	0.9738	0.8717
[22]	0.9576	0.8907	0.9493	0.7366	-	-
[12]	0.9681	0.8653	-	-	0.9434	0.8570
[24]	0.9644	-	0.9105	-	0.9789	-
[27]	0.9840	0.7893	0.9831	0.7590	-	-
[32]	-	-	0.9650	0.9620	-	-
[26]	-	-	0.8611	0.8507	-	-
This work	**0.9929**	0.8777	**0.9833**	0.8321	0.9812	**0.8921**

information to effectively support forwarding decisions. To enhance the utility of predictions, it is therefore desirable to forecast links over extended time horizons, thereby offering a more comprehensive view of network evolution. In this context, predicting multiple consecutive adjacency matrices becomes essential for capturing network dynamics over longer periods.

To evaluate the model's ability to predict multiple future matrices, experiments were conducted using a subset of the MIT Reality Mining dataset. This dataset was selected due to its substantially longer duration compared to the ITC and Infocom06 datasets, making it particularly suitable for assessing forwarding strategies in opportunistic networks. In these experiments, the model was provided with an input sequence of ten adjacency matrices and tasked with predicting ten consecutive future matrices, enabling the evaluation of its performance over extended time intervals. Using the adopted notation, given the input sequence, $A^{t:t+9} = \{A^t, A^{t+1}, \ldots, A^{t+9}\}$, the model predicts the subsequent sequence $A^{t+10:t+19} = \{A^{t+10}, A^{t+11}, \ldots, A^{t+19}\}$.

The mean AUC and PRAUC values obtained during the test phase with the 2D CNN model are presented in Table 4. Both metrics exhibit a gradual decline as predictions extend further into the future, reflecting the increasing difficulty of forecasting links over longer time horizons. The decline in PRAUC is more pronounced than that observed for AUC, which can be attributed to the severe class imbalance present in the dataset. While the baseline for AUC is 0.5, corresponding to the expected performance of a random classifier [8], the baseline for PRAUC is determined by the prevalence of the positive class [19], which in this case is approximately 0.0014. Consequently, PRAUC provides a more informative assessment of the model's ability to correctly predict rare positive links in highly imbalanced datasets.

Table 4. MIT Dataset Link Prediction for Multiple Future Matrices

Prediction Window	Time (s)	AUC	PRAUC
1	0—300	0.9781	0.8822
2	300—600	0.9542	0.7682
3	600—900	0.9418	0.6702
4	900—1200	0.9211	0.5946
5	1200—1500	0.9064	0.5351
6	1500—1800	0.8895	0.4861
7	1800—2100	0.8752	0.4362
8	2100—2400	0.8564	0.3937
9	2400—2700	0.8537	0.3545
10	2700—3000	0.8503	0.3251

5 Discussion

This work addresses the problem of link prediction in opportunistic networks, focusing on the development of techniques to predict future links to improve packet forwarding while preserving network resources. The adopted approach represents network dynamics by partitioning contact records into discrete time intervals and modeling them as adjacency matrices.

This study has two main objectives. The first is to evaluate the 2D CNN model proposed by [27] on three real-world opportunistic network datasets by predicting the next adjacency matrix from a sequence of previous matrices. The second is to assess the model's performance in a longer-term prediction scenario by forecasting the next ten consecutive future matrices from an input sequence of ten matrices using the MIT Reality Mining dataset.

The results indicate that the 2D CNN model achieved superior performance on the Infocom06 and MIT Reality Mining datasets, with AUC values of 0.9823 and 0.9812, and PRAUC values of 0.8321 and 0.8921, respectively. Furthermore, multi-step prediction results show a gradual decline in performance as the prediction horizon increases. Nevertheless, even for the tenth predicted matrix, results remain significantly above the baseline values of the evaluation metrics. Specifically, the AUC of 0.8503 is 170% higher than the baseline of 0.5, and the PRAUC of 0.3251 is 23,221% higher than the baseline of 0.0014.

These findings suggest that long-term link prediction using the 2D CNN model can provide meaningful insights into future connectivity patterns in opportunistic networks. This capability may support more effective forwarding decisions in routing protocols, potentially improving network efficiency.

6 Conclusions

This paper evaluated a 2D CNN-based approach for link prediction in opportunistic networks using real-world datasets. The results demonstrate that the

model effectively predicts future network connections, achieving strong performance across different scenarios and maintaining reasonable accuracy even for longer-term predictions. Overall, the findings indicate that deep learning-based approaches, particularly those employing temporal patterns in the sequence of adjacency matrices, represent a promising direction for improving link prediction and supporting routing strategies in opportunistic networks.

As directions for future work, several research avenues can be explored to further improve the proposed approach. First, conducting sensitivity analyses of the 2D CNN architecture with respect to key parameters is recommended. These parameters include the temporal window size used in generating adjacency matrices from the dataset records, as well as the length of the input matrix sequences used for predictions. Such analyses can provide deeper insight into how these factors influence model performance and help guide the selection of more effective configurations, ultimately improving the overall approach.

Additionally, it is important to investigate how adapting the current model to more advanced deep learning architectures, such as graph neural networks and temporal graph networks, would affect link prediction performance and the associated training cost. Another promising direction is the exploration of online or continual learning strategies, enabling the model to dynamically adapt to evolving network conditions over time.

Furthermore, it is important to investigate the use of multi-step future adjacency matrix predictions in message forwarding protocols. This approach aims to reduce the number of message copies by enabling more informed selection of the next forwarding node. The proposed protocol could be evaluated in simulation environments using the MIT Reality Mining dataset, allowing its effectiveness to be assessed under realistic network conditions.

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